The impact of future warming on global rice yield

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Rice is the staple food for more than 50% of the world's population[1-3]. Reliable prediction of changes in rice yield is thus central for maintaining global food security. Here, we compare the sensitivity of rice yield to temperature increase derived from field warming experiments and three modelling approaches: statistical models, local crop models and global gridded crop models. Field warming experiments produced a substantial rice yield loss under warming, with an average temperature sensitivity of -5.2±1.4% K^{-1}. Local crop models gave a similar sensitivity (-6.3±0.4% K^{-1}), but statistical and global gridded crop models both suggest less negative impacts of warming on yields (0.8±0.3% K^{-1} and -2.4±3.7% K^{-1}, respectively). Using data from field warming experiments, we further propose a conditional probability approach to constrain the large range of global gridded crop model results for the changes in future yield in response to warming by the end of the century (from -1.3% K^{-1} to -9.3% K^{-1}). The constraint implies a more negative response to warming (–8.3±1.4% K^{-1}) and reduces the spread of the model ensemble by 35%. This yield reduction exceeds that estimated by the International Food Policy Research Institute assessment (-4.2 to -6.4% K^{-1})[4]. Our study suggests that without CO_2 fertilization,

effective adaptation and genetic improvement, severe rice yield losses are plausible under intensive climate warming scenarios.

Hunger and malnutrition are two alarming problems calling for increased yields[5,6]. Rice is currently one of the most widely grown crops in the world and the main source of calories in developing countries[1-3]. Any reduction in rice productivity could, therefore, have dramatic implications for global food security[5]. Climate warming exceeding the optimum physiological temperature of rice plants has been shown to cause such a reduction[7,8]. The assessment of food security from the International Food Policy Research Institute (IFPRI) also stated that climate change, without the separate effects of CO_2 fertilization, would cause a 10-12% reduction of irrigated rice yield globally by 2050[4]. Unfortunately, we have poor understanding of the physiological mechanisms through which rice plants may respond to climate change. Many studies are using process-based crop models to project climate change impacts on crop yields[9–10]. These models integrate plant-scale physiological mechanisms, and can be run at site, regional or global scale with forcing variables derived from global climate models under different greenhouse gas emission scenarios. Yet, the parameters of crop models are usually not measured across the full scale of model applications, and model equations may also be wrong, leading to large uncertainties in projections of future climate change impacts [10-12].

The Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP-1)[13] and the Agricultural Model Intercomparison and Improvement Project (AgMIP)[14] coordinated multi-model simulations of the yields of major crops, including rice. One of the findings of AgMIP is that multi-model mean or median values give better simulations of the observed yield of rice[15] than any individual model, but it remains unclear whether the 'average model' is meaningful at all. Errors in parameter values, as well as in model structure, result in large model-to-model variation in simulated yield[10]. However, if the bias of a model for the present persists into the future, an emerging constraint can be established through which present-day observations can be used for eliminating less realistic models in the simulation of temperature response; this reduces the uncertainty in the ensemble projection. This heuristic approach called 'emerging constraint' has been applied to constrain simulations, e.g., of the sensitivity of the tropical carbon cycle and of snow albedo, to temperature[16,17]. Here, to reduce the large range of the ISI-MIP1 global gridded crop models (GGCMs)[18] for the sensitivity of rice yield to temperature, we use a new compilation of data from 83 field warming experiments at 13 sites over the globe (Supplementary Table 1) (see Methods).

Five GGCMs driven by daily weather outputs from five climate models (CM) (see Methods) were run under the high warming Representative Concentration Pathway RCP8.5 (2070-2099) scenario, with CO_2 fixed at the present-day value (excluding the relevant benefits from CO_2 fertilization in the future). This procedure allows us to estimate the effect of climate change alone on yield. The five climate models used to drive the GGCMs, gave an increase in growing-season mean air temperature over ricegrowing areas ranging from 3.3 K (GFDL-ESM2M) to 5.0 K (IPSL-CM5A-LR) relative to today (Fig. 1a). The median value of the climate-induced rice yield change was -27% (Fig. 1b) — a large yield reduction which would pose a threat to future food security. However, the range of model responses was large, reflecting uncertainties in climate projections and in GGCMs, with yield reductions ranging from 6.6% in LPJGUESS+HadGEM2-ES to 42.4% in EPIC+HadGEM2-ES (see also ref.18). Dividing the changes in yield by the magnitude of temperature warming above present-day values defines the long-term sensitivity of rice yield to warming by the end of the twenty-first century (,). This sensitivity was negative for all combinations of GGCM and climate model, and ranged from -1.3% K^{-1} with LPJ-GUESS+HadGEM2-ES to -9.3% K^{-1} with EPIC+HadGEM2-ES; the median value was -6.5% K^{-1}.

Then, for each GGCM-CM pair, we also calculated the present-day interannual temperature sensitivity of rice yield (,) for the model grid cells where the field experiments were located, using multiple linear regression models to separate the sensitivity of modelled yields (1971-2000) to growing-season temperature, precipitation and radiation. Figure 2a shows that there is an emerging strong linear relationship (R^2=0.75, P<0.001) between long-term (,) and present-day interannual (,) sensitivities of yield to temperature across all GGCM-CM combinations. This means that a model showing a high negative yield response to warm years during the last 30 years also projects a high warming-induced yield decrease in the future. This implies that the GGCM responses to temperature are generally conserved between historical and future conditions.

To assess the realism of these modelled yield sensitivities to warming, we compiled data from field experiments where rice plots were warmed (Supplementary Table 1). More than 80% (67 out of 83) of the field experiments reported a rice yield loss under warming, with an average observed sensitivity of yield to warming (,) of -5.2±1.4% K^{-1} (Fig. 3). According to the ‘emerging constraint’ method (see Methods), these field experiments provided an observation-based probability density function (PDF) for modelled ,, and the linear relationship between , and , (Fig. 2a) provided another PDF of , for a given , . The conditional probability of modelled , that is consistent with the PDF of observed sensitivities (red dashed line in Fig. 2b) gives a PDF of constrained modelled ,. The maximum likelihood value of this constrained , sensitivity was more negative (–8.3±1.4% K^{-1}) than the one of the original model ensemble (Fig. 2b), and the 1-sigma uncertainty of the PDF of , was reduced by 35%. This means that the information from field warming experiments shifts the modelled long-term temperature sensitivities of rice yield towards more negative values, and reduces the variation among models. When applying the same emerging constraint of the conditional probability to the model grid cells of the experimental sites, or to the grid cells with similar climate or similar rice yield, the constrained , values in all cases were more negative than the original ensemble of models, and had a lower uncertainty (Supplementary Fig. 1).

The temperature sensitivities obtained from field experiments can also be considered as realistic analogues of GGCM long-term sensitivities, because both approaches consider a warming over ambient conditions of similar magnitude. Replacing the present-day temperature sensitivities (,) over the GGCM grid cells of experimental sites (horizontal-axis variable) with that of the long-term ones (,) in Fig. 2, we found that the experimentally constrained , was -7.2±1.5% K^{-1}, still less uncertain and more negative than the unconstrained value reflecting the spread of all the GGCMs forced by different climate models (Supplementary Fig. 2).

With the emerging constraint approach of this study, it is important to assess all the uncertainties that might bias the final result. For instance, some experiments included multiple warming treatments and nutrient levels. We thus verified that , depends neither on the magnitude of warming applied (Supplementary Fig. 3, P>0.1), nor on the background growing-season temperature (Supplementary Fig. 4, P>0.1) or nutrient levels (Supplementary Fig. 5, P>0.1) across the set of experiments we have compiled. In addition, field experiments had different designs and used different techniques to warm the plots. Passive warming techniques using greenhouses or open-top-chambers were criticized because they also alter light, wind, and soil moisture[19,20]—active warming techniques using artificial heaters are considered more reliable[20,21]. When only the results from active warming experiments were used (Supplementary Fig. 6), the constrained , was -7.0±1.7% K^{-1}, remaining more negative than the unconstrained value, but the uncertainty reduction achieved for model results was smaller (only 19% against 35% with all experiments), which is attributed mainly to the small number of active warming experiments published so far (only five sites; Supplementary Table 1).

A second source of uncertainty in our approach is that the values of , derived from model simulations represent the average yield change divided by the average temperature increase averaged over many years with non-uniform warming across the growing season, whereas field experiments last only a few years. Using individual years, instead of the average of the last 30 years of the twenty-first century, to calculate ,, the constrained , remained less uncertain and more negative than the unconstrained value for 29 individual years (Supplementary Fig. 7). Our result is thus robust and not sensitive to the method used to define the long-term yield sensitivity to warming in model outputs. In addition, warming experiments located in the US (24 out of 83 experiments, Supplementary Table 1) might be not representative of the varieties, edaphic and climate conditions over today's dominant rice growing regions in Asia. However, even when using only the experiments performed on Asian rice varieties, with only the GGCM grid cells of these regions, the emerging linear relationship between , and , was still present (Supplementary Fig. 8, R^2=0.74, P<0.001), and the constrained , was -6.9±1.4% K^{-1}, less uncertain than the unconstrained value (-5.8±2.0% K^{-1}).

Why does the ISI-MIP-1 ensemble median of pairs of GGCMs and climate models underestimate rice yield losses in response to warming (Fig. 2b)? One reason might be the inclusion of adaptation in some GGCMs. For instance, LPJ-GUESS assumes very flexible adaptation in growing-season lengths, i.e., plasticity of cultivars, and GEPIC allows for adaptation in sowing dates. Removing these two models from the constraint, does not remove this underestimation (Supplementary Fig. 9), suggesting that the fact that some models include a degree of adaptation does not eliminate the underestimated , in GGCMs. Also, the use of CM-based climate scenarios with non-uniform warming across the growing season and where also changes in radiation and precipitation are included, can lead to a veiled temperature response. As most of the rice production is fully irrigated, we assume that the temperature signal is the dominant climate impact also in the CM-driven GGCM simulations. Another reason could be that the ensemble did not contain a sufficiently large enough number of crop models (five in our study). All the possibilities of current rice models may not have been included and this would hamper the strength of the model ensemble[10,15]. Fortunately, a larger number of crop models will be used in the Phase II of ISI-MIP/AgMIP; this will allow a further test of the robustness of the emerging constraint approach.

Independently from field warming experiments and GGCMs, there are also a large number of publications from local crop models used to interpret field trials (arguably those models are well calibrated to specific rice varieties and cultivation practice) and from statistical models where the sensitivity of rice yield to temperature change is derived from observed interannual variability. These different temperature sensitivities are shown in Fig. 3 for the present-day period and the future (end of the century). For the present-day sensitivities, 95% of local crop model simulations (329 studies out of 346) give a negative response to warming, with a mean sensitivity of –6.3±0.4% K^{-1}, more negative but consistent with the values inferred from field warming experiments (-5.2±1.4% K^{-1}). Statistical models have a surprisingly lower percentage of studies (46 studies out of 77) presenting negative , than warming experiments (more than 80% of studies), and also give a weaker mean sensitivity (,= –0.8±0.3% K^{-1}; Fig. 3) than both warming experiments and local crop models. This weak sensitivity might be due to the aggregated nature and disputable quality of historical yield and weather data in different regions[22], to difficulties in separating the temperature effect from co-varying management practice[23], increasing CO_2, and to non-linearity in the temperature response[24]. Lower sensitivities are also found in the GGCM results during the presentday period compared to the long term (Fig. 3). This suggests that GGCMs have thresholds above which the temperature response of rice yield becomes significantly more negative (see also ref. 18).

We also compared our , value with that implied from IFPRI (as a representative of the policy community) who project the future of the world's food supply. They predicted 10 and 12% losses of global rice yield by 2050, based on temperature increase scenarios of 1.5 ^{o}C and 2.9 ^{o}C, respectively[4]. Thus a rough estimate of the sensitivity of rice yield to warming is -4.2 to -6.4% K^{-1}, a smaller magnitude than that from the global crop models constrained by experimental data in our study (-8.3±1.4% K^{-1}). However, we noted that the constrained , derived here was for the end of this century (2070-2099), inconsistent with the time frame used by IFPRI (2050s). When applying the emerging constraint to the time frame of midcentury (2036-2065), the constrained , was -8.5±2.3% K^{-1} (Supplementary Fig. 10) — still a larger magnitude than the number from IFPRI. This result suggests that warming appears to present an even greater challenge to rice than expected and more effective adaptation strategies are thus required.

The prediction of yield loss under future warming notably does not consider otherthan-climate factors that could sustain or increase yield, in particular increased CO_2[25,26], adaptation[11,27] and improved management/cultivars that are independent of adaptation to warmer temperatures[28]. For instance, the current rates of genetic gains in yield for hybrid rice are 0.6-0.7% yr^{-1} [28]. In our study, the results from the global gridded crop model constrained by observations suggest a yield loss of 37% for the end of the century due to increased temperature under the RCP8.5 scenario (multiply the constrained sensitivity in Fig. 2 by climate warming in Fig. 1), but the loss will unfold over 70 years, i.e., at an average rate of 0.5% yr^{-1}. The genetic improvement sustained during one century at current rates could thus offset the negative impact from increased temperature. To fulfil the projected increase in cereal demand for the world population (~1.2% yr^{-1})[29], however, the increase in rice yield from technological change, together with the CO_2 effect and adaptation, would need to be much higher (1.7% yr^{-1}) to offset the development of negative effects of climate change at a rate of 0.5% yr^{-1}.

Our study, combining field warming experiments with three modelling approaches, comprehensively assessed the global response of rice yield to warming. The main result is that all approaches indicated a decrease in rice yield in response to warming, and the field warming experiments suggested an even higher risk of future yield reductions than that inferred from unconstrained GGCM results. Future experiments with standard measurement protocols, long time periods and a large range of rice genotypes and management types[30] should provide more insight on constraining modelling results. Our results, however, show that warming under climate change poses a significant threat to rice production and thus to a major staple food with substantial impact on the food security of developing and emerging economies. The long-term perspective of climate change allows us to prepare agricultural production systems for this challenge, but suitable policies must be put in place in the near future, given that targeted research on adaptation options and their large-scale implementation will require considerable time.

Methods

ISI-MIP data set. Starting in 2012, the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP-Phase 1 project; *isi-mip.org*) used multi-model ensembles to assess the climate change impacts across multiple sectors. In the agriculture sector, multiple global gridded crop models (GGCMs)[18] were used to simulate crop yield. We used yield simulated by five GGCMs (EPIC, GEPIC, LPJ-GUESS, LPJmL and pDSSAT). These model outputs are available as annual time series at a spatial resolution of 0.5×0.5 degrees. GGCM simulations were driven by historical (1971–2005) and future (2006–2099) climate forcing including temperature, precipitation and solar radiation. These forcing data were taken from a bias-corrected climate data set based on five climate models (CMs) in the Coupled Model Intercomparison Project Phase 5 (CMIP5)[31]. Of the ISI-MIP crop model ensemble, PEGASUS did not provide yield data for rice and GAEZ-IMAGE was excluded because its modelling approach does not provide sufficient information on interannual variability to calculate the temperature sensitivity of rice yield. More detailed information about the five GGCMs which were used can be found in ref.18. The high-emission scenario, representative concentration pathway (RCP) 8.5 was chosen as it not only represents the upper end of projected climate change, but also provides the largest ensemble of GGCM-CM combinations to consider the broadest possible range of climate impacts. GEPIC and LPJ-GUESS only contributed data for one CM (i.e., HadGEM2-ES) and thus a total of seventeen GGCMCM combinations were used in our analysis. All GGCM-CM simulations used here were conducted with constant CO_2 concentration and current management (see ref. 18 for exceptions). We used the model output for the full irrigation scenario, since irrigated rice currently makes up about 75% of world production[3].

Literature review. We searched peer-reviewed and primary research from Web of Science, Google Scholar and China National Knowledge Infrastructure (CNKI, http://www.cnki.net) that was published before January 2015. All publications related to the responses of rice yield to temperature change were considered. Three main approaches were distinguished, namely, local process-based crop models, statistical models and field warming experiments. To obtain the sensitivity of rice yield to temperature (,; yield change per K), local process-based models usually conduct an arbitrary sensitivity test (e.g., +2 ^{o}C scenario), with other conditions kept constant; whereas statistical models use regression equations to relate historical records of rice yield to weather including temperature. On the other hand, field warming experiments apply direct warming treatments to rice in field plots. , is calculated as :

$$, = \Delta Y/\Delta T \qquad (1)$$

where ΔY and ΔT are the rice yield change and temperature change, respectively. The average , and its uncertainty for experiments are obtained from bootstrap resmpling. Here we assume the experimental data (Supplementary Table 1) as: $X=\{X_1, X_2, \ldots, X_n\}$, where X_n represent all the experiments at site n. The steps of bootstrapping are as follows: (1), resample one experiment at each site to obtain a bootstrap resample: $X_1*=(x_1, x_2, \ldots, x_n)$, where x_n represent the sampled experiment at site n. (2), compute the mean of this resample and obtain the first bootstrap mean: $\mu_1*=\frac{1}{n}\sum$. (3), repeat the process of (1) and (2) to obtain the second resample X_2* and compute the second bootstrap mean μ_2*. Repeating this 5000 times, we have μ_1*, μ_2*, …, $\mu_{5000}*$, which constitute an empirical bootstrap distribution of sample mean. Here each $\mu*$ represents one case of average sensitivity for all the sites (Supplementary Fig. 11). The difference between $\mu*$ values is from the use of different experiment within sites. Therefore, the PDF now reflects the variations caused by different experiments within sites.

Constraint. Our constraint methodology comes from Cox *et al.*[16], who built an emergent linear relationship between the sensitivity of tropical land-carbon storage to warming and the sensitivity of the annual growth rate of atmospheric CO_2 to tropical temperature anomalies across models. They then used the historical observed CO_2 growth rate sensitivity to temperature to constrain the uncertainties of future climate impact on tropical carbon through the conditional probability approach. Here we used a similar approach, first building the relationship between the historical temperature sensitivity of crop yield and the future yield feedbacks across the GGCM modelensembles, and then using the observed field warming experiments to constrain future modelled yield-climate feedbacks. The details of the constraint methods are described in Supplementary Methods. It should be noted that the PDF of GGCM-CM could be biased, because some crop models (GEPIC and LPJ-GUESS) were only paired with one CM (HadGEM2-ES). This unbalance in the selection of the GGCM-CM combination was checked with five GGCMs but with random selection of different CMs, i.e., one pair of GGCM-CMs with random CM selection (Supplementary Fig. 12).

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Author contributions

S.L.P. designed research; C.Z. performed analysis; and all authors contributed to the interpretation of the results and the writing of the paper.

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Figure legends

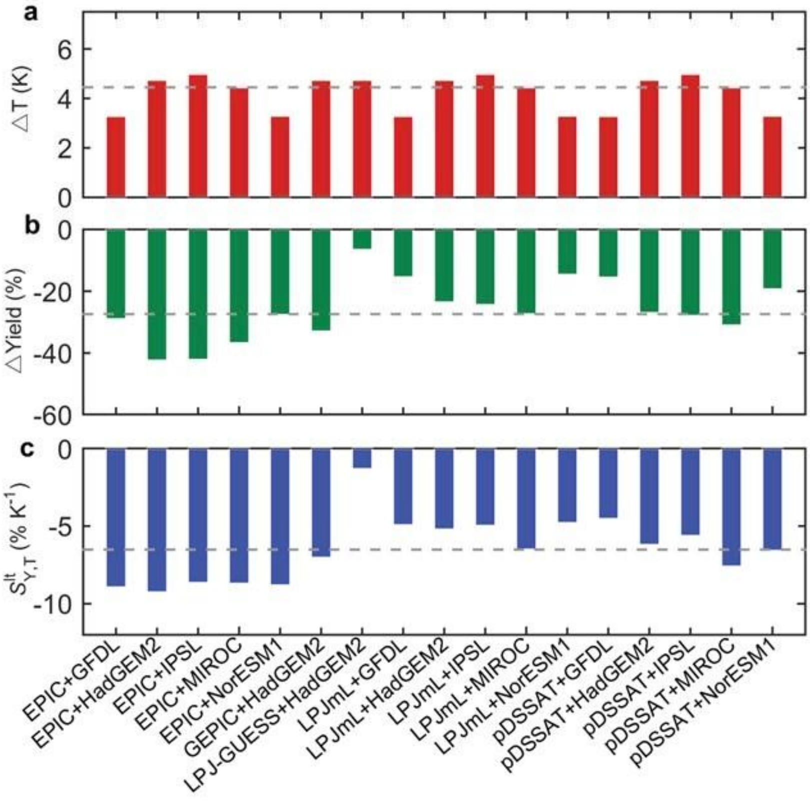
Figure 1. Future climate change (2070–2099, RCP 8.5) and its impact on global rice yield (in comparison to 1971–2000 baseline) from an ensemble of seventeen GGCM-CMs without CO_2 fertilization effects. a, Growing-season temperature change. **b**, Relative yield change (reproduced by ref.18). **c**, The sensitivity of rice yield to climate change (,). The dashed lines represent the median value of the ensemble. GFDL, HadGEM2, IPSL, MIROC, and NorESM1 represent the climate models GFDLESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM and NorESM1-M, respectively.

Figure 2. Constraint on the long-term sensitivity of rice yield to temperature change. a, The relationship between global long-term temperature sensitivity of rice

yield (,) and site-scale present-day rice yield sensitivity to temperature across an ensemble of seventeen GGCM-CMs. The red line shows the temperature sensitivity estimates (, mean ± standard deviation) from field warming experiments. **b**, Probability distribution of ,. The black line in **b** is the probability distribution of unconstrained ,, assuming all the components of the ensemble can be represented by a Gaussian distribution; the red dashed line is the experimental data-constrained probability distribution of ,.

Figure 3. The estimates of , from four distinct approaches: global gridded crop models (GGCMs), local crop models, statistical models and field warming experiments. **a**, Map of the study sites from local crop models, statistical models and field warming experiments. The regional-scale studies are represented by the corresponding label in the centre of the region (one global-scale study is not shown). **b**, The estimates of all the present-day and long-term ,. The , from GGCMs are averages of all the global grid cells but not the grid cells where field warming experiments are located. Error bars show the standard deviation.

Figure 1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△T (K)
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$S^{lt}_{Y,T}$ (% K^{-1})
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-10
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EPIC+HadGEM2
EPIC+IPSL
EPIC+MIROC
EPIC+NorESM1
GEPIC+HadGEM2
LPJ-GUESS+HadGEM2
LPJmL+GFDL
LPJmL+HadGEM2
LPJmL+IPSL
LPJmL+MIROC
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Figure 2

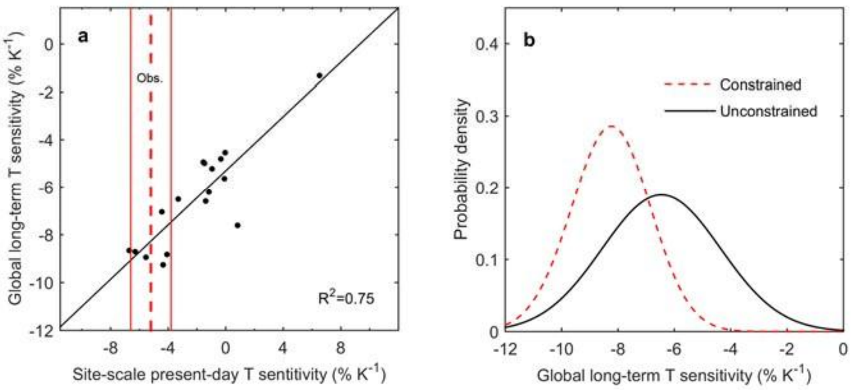
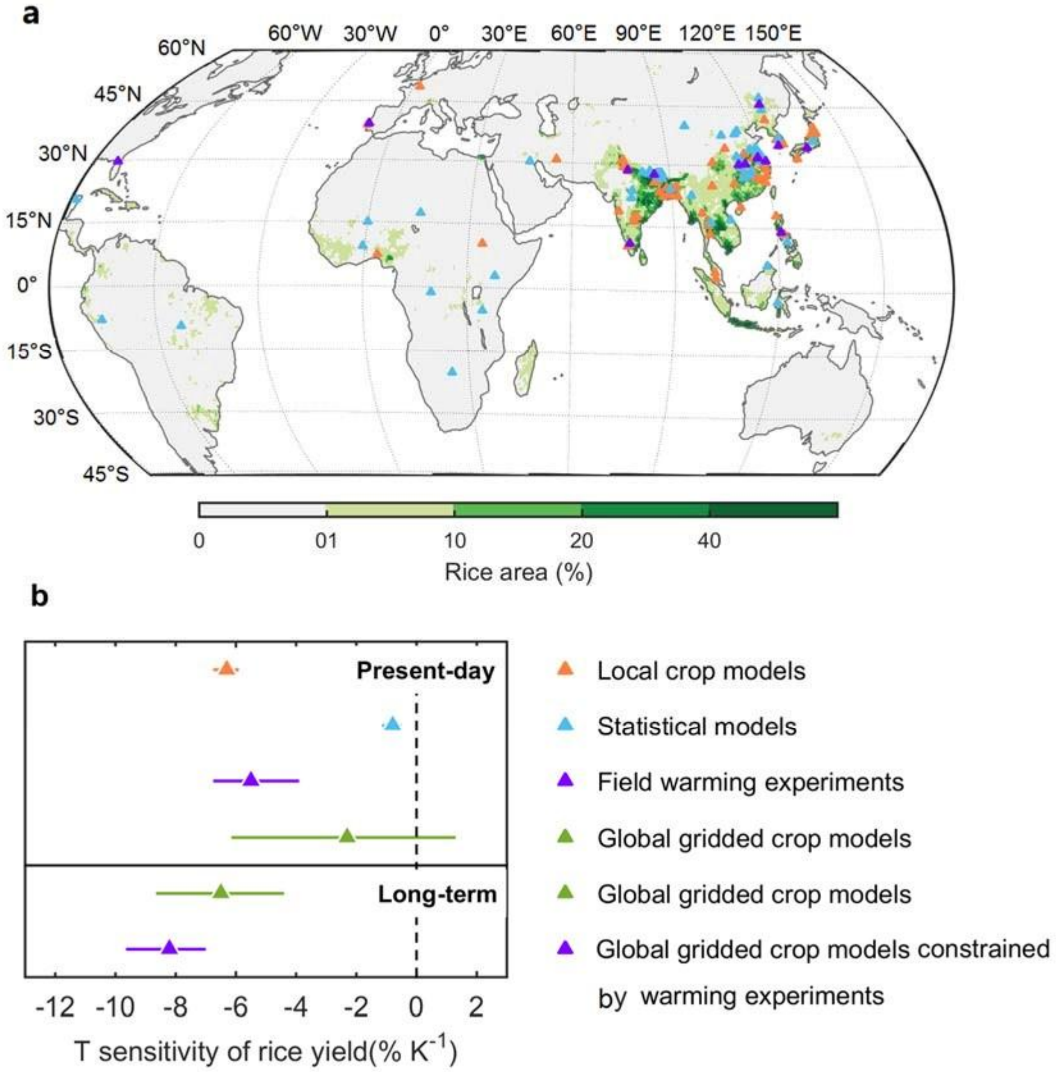

a
Obs.
R2=0.75
Global long-term T sensitivity (% K-1)
Site-scale present-day T sentitivity (% K-1)
b
Constrained
Unconstrained
Probability density
Global long-term T sensitivity (% K-1)

Figure 3


a
60°W 30°W 0° 30°E 60°E 90°E 120°E 150°E
60°N
45°N
30°N
15°N
0°
15°S
30°S
45°S
0
01
10
20
40
Rice area (%)
b
Present-day
Long-term
-12 -10 -8 -6 -4 -2 0 2
T sensitivity of rice yield(% K-1)
Local crop models
Statistical models
Field warming experiments
Global gridded crop models
Global gridded crop models
Global gridded crop models constrained by warming experiments